Explaining Credit Default Swap Spreads with Equity Volatility and Jump Risks of Individual Firms*

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Abstract

This paper explores the effects of firm-level volatility and jump risks on credit spreads in the credit default swap (CDS) market. We use a novel approach to identify the realized jumps of individual equity from high frequency data. Our empirical results suggest that the volatility risk alone explains 50% of CDS spread variation, while the jump risk alone explains 23%. After controlling for ratings, macro-financial variables, and firms' balance sheet information, we can explain 75% of the total variation. These findings are in sharp contrast with the typical lower predictability and/or insignificant jump effect in the credit risk market. Moreover, firm volatility and jump risks show important nonlinear effect and strongly interact with the firm balance sheet information, which is consistent with the structural model implications and helps to explain the so-called credit premium puzzle.

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1 Introduction

Structural-form approach on the pricing of credit risk can provide important economic intuitions on what fundamental variables may help to explain the credit default spread. The seminal work of Merton (1974) points to the importance of leverage ratio, asset volatility, and risk-free rate in explaining the cross-section of default risk premia. Subsequent extensions in literature include the stochastic risk-free interest rate process proposed by Longstaff and Schwartz (1995); endogenously determined default boundaries by Leland (1994) and Leland and Toft (1996); strategic defaults by Anderson et al (1996) and Mella-Barral and Perraudin (1997); and the mean-reverting leverage ratio process in Collin-Dufresne and Goldstein (2001). These generalizations call for time-varing macro-financial variables and firm specific accounting ratios as key determinants of the credit risk spreads. Further development of the jump–diffusion default model along the lines of Zhou (2001) indicates that jump intensity and volatility risks of firm value should have a strong impact on the credit spreads.

Despite the theoretical insights in understanding default risk, the empirical performance of structural-form models is far from satisfactory. There has been recently a burgeoning literature that points to the large discrepancy between the predictions of structural models and the observed credit spreads, which is also known as the credit premium puzzle (Amato and Remolona 2003). For instance, Huang and Huang (2003) calibrate a wide range of structural models to be consistent with the data on historical default and loss experience. They show that in all models credit risk only explains a small fraction of the historically observed corporate-treasury yield spreads. In particular, for investment grade bonds, structural models typically explain only 20-30% of observed spreads. Similarly, Collin-Dufresne et al (2001) suggest that default risk factors have rather limited explanatory power on variation in credit spreads, even after the liquidity consideration is taken into account. A recent study by Eom et al (2004) finds that structural models do not always under-predict the credit spreads, rather, those models produce large pricing errors for corporate bonds. Incorporating jump risks has been helpful in explaining the level of credit spreads of investment-grade entities with short maturities (cite?), however, historical skewness as a measure of jump risks is usually insignificant statistically or having the wrong sign (cite?).

In this paper, we argue that the unsatisfactory performance of structural models may be partially attributed to the fact that the impacts of volatility and jump risks are not treated seriously in the previous studies. A prevalent practice is to use the average equity volatility within each rating category in calibration, which is subject to the "Jensen inequality" problem if the true impact of volatility on credit spreads is not linear. Even when firm-level equity volatility is used, historical volatility based on daily equity returns is often used, which tends to smooth out the short term impact of volatility on credit spreads, especially the jump risk impacts. More importantly, when jump effect is measured as historical skewness, it may over-detect a model with asymmetric distribution but no jumps while under-detect a model with symmetric jump distributions. The idea of emphasizing the links between equity volatility or jump risks and credit spreads is not completely new. Campbell and Taksler (2003) and Kassam (2003) observe that recent increases in corporate yields can be explained by the upward trend in idiosyncratic equity volatility. This observation is consistent with our findings in the this paper. Collin-Dufresne et al (2003) suggest that the jump risk alone does not explain a significant proportion of the observed credit spreads of aggregate portfolios. Instead, its impact on the contagion risk turns out to be associated with a much larger risk premium. Cremers et al (2004a, 2004b) measure volatility and jump risk from prices of equity index put options. They find that adding jumps and jump risk premia significantly improve the fit between predicted credit spreads and the observed ones.[1]

Our contribution is to use high frequency return data of individual firms to decompose the realized volatility into a continuous part RV(C) and a jump part RV(J). With stronger assumptions, we are able to filter out the realized jumps and isolate the impacts associated with jump intensity, jump volatility, and negative jumps. Therefore we can examine the credit spreads more thoroughly with short term volatility and various jump risk measures, in addition to the long-run historical volatility. Recently literature suggests that realized volatility measures from high frequency data provides a more accurate measure of the short term volatility (Andersen et al 2001, Barndorff-Nielsen 2002, and Meddahi 2002). Within the realized volatility framework, the continuous and jump contributions can be separated by comparing bi-power variation (from adjacent returns) and quadratic variation (from squared returns) (see, Barndorff-Nielsen and Shephard 2004, Andersen at el 2004, and Tauchen and Huang 2005, for the discussion of this methodology). Considering that jumps in financial prices are usually rare and of large sizes, we further assume that (1) there is at most one jump per day, and (2) jump size dominate daily return when it occurs. With filtered daily jumps, we further estimate the jump intensity, jump mean (further decomposed into positive and

[1] In this paper, we refrain from using option-implied volatility and jump measures, because they are already embedded with risk premia, which may have similar time-variation as credit spreads and need to be explained by the same underlying risk measures as well.

negative parts), and jump volatility. We apply these new volatility and jump risk measures in to explain the credit default swap spreads.

Our empirical results suggest that long-run historical volatility, short-run realized volatility (continuous), and various jump risk measures all have statistically significant and economically large impacts on the credit spreads. The realized jump measures explain 23% of total variations in credit spreads, while historical skewness and kurtosis measures on jump risk only explain 3%. It is worth noting that volatility and jump risk alone predict 53% of spreads variations. After controlling for ratings, macro-financial variables, and firms' accounting information, the signs and significances of jump and volatility impacts remain solid, and the R-square increases to 75%. These results are robust whether fixed effect or random effect is taken into account. More importantly, both volatility and jump risk measures show strong nonlinear effects, which suggests that the practice of using aggregate volatility across board or within rating groups could either overestimated or underestimate the true impact from individual firms. Finally, but not least, jump and volatility risk interact prominently with rating groups and firm-specific financial variables. This evidence indicates that the strong predictability of jump and volatility variables are not merely a statistical phenomenon, rather, they reflect the financial market assessment of firms' economic value and financial health. In particular, the interaction between volatility & jump risks with the quoted recovery rate suggests that credit default spreads have priced in the time-varying recovery rates. These findings are consistent with a limited simulation exercise from stylized structural models, and may help to resolve the so-called credit premium puzzle.

The remainder of the paper is organized as follows. Section 2 introduces the methodology for disentangling volatility and jump risks with high frequency data. Section 3 gives a brief discussion of data, and Section 4 examines the main empirical findings. A limited simulation exercise is presented in Section 5, and Section 6 concludes.

2 Disentangling Jump and Volatility Risks

Equity volatility is central to asset pricing and risk management. Traditionally, researchers have used the historical volatility measure, which are constructed from daily returns. A daily return r_t is defined as the first difference between the log closing prices on consecutive trading days (P_t), that is

$$r_t \equiv \log P_t - \log P_{t-1} \tag{1}$$

Historical volatility and historical skewness, which are defined as the variance and skewness of the daily return series over a given time horizon, are considered as proxies for the volatility and jump risk measures of the stochastic process of the underlying asset (for example, see Campbell and Kassam 2003 and Cremers et al 2004a, 2004b).

In recent years, given the increased availability of high-frequency financial data, a number of scholars, including Andersen and Bollerslev (1998), Anderson et al (2001, 2003), Barndorff-Nielsen and Shephard (2002a, 2002b), and Meddahi (2002), have advocated the use of so-called realized volatility measures by utilizing the information in the intra-day data for measuring and forecasting volatilities. More recent work on bi-power variation measures, which are developed in a series of papers by Barndorff-Nielsen and Shephard (2003a, 2003b, 2004), allows the use of high-frequency data to untangle realized volatility into continuous and jump components, as in Andersen et al 2004 and Huang and Tauchen 2005. In this paper, we rely on the stylized fact that jumps on financial markets are rare and of large size, to explicitly estimate the jump intensity, jump variance, and jump mean (positive and negative), and to assess more explicitly the impacts of volatility and jump risks on credit spreads.

Let p_t denote the time t logarithmic price of the asset, and it evolves in continuous time as a jump diffusion process:

$$dp_t = \mu_t dt + \sigma_t dW_t + \kappa_t dq_t \tag{2}$$

where μ_t and σ_t are the instantaneous drift and volatility, W_t is the standard Brownian motion, dq_t is jump process with intensity λ_t, and $\kappa(t)$ refers to the size of the corresponding (log) jumps.[2] Time is measured in daily units and the intra-daily returns are defined as follows:

$$r_{t,j} \equiv p_{t,j\cdot\Delta} - p_{t,(j-1)\cdot\Delta} \tag{3}$$

where $r_{t,j}$ refers to the j^{th} within-day return on day t, and Δ is the sampling frequency.[3]

Barndorff-Nielsen and Shephard (2003a, 2003b, 2004) propose two general measures to the quadratic variation process, realized volatility and realized bipower variation, which

[2] A standard assumption is that κ_t observes a normal distribution.

[3] That is, there are $1/\Delta$ observations on every trading day. Typically the 5-minute frequency is used because more frequent observations might be subject to distortion from market microstructure, which may distort the properties of asset returns.

converge uniformly (as $\Delta \to 0$) to different quantities of the jump-diffusion process,

$$RV_t(\Delta) \equiv \sum_{j=1}^{1/\Delta} r_{t,j}^2 \to \int_{t-1}^{t} \sigma_s^2 ds + \sum_{j=1}^{1/\Delta} \kappa_{t,j}^2 \tag{4}$$

$$BV_t(\Delta) \equiv \frac{\pi}{2} \sum_{j=2}^{1/\Delta} |r_{t,j}| \cdot |r_{t,j-1}| \to \int_{t-1}^{t} \sigma_s^2 ds \tag{5}$$

Therefore the difference between realized volatility and bipower variation is zero when there is no jump and strictly positive when there is a jump. A variety of jump detection techniques are proposed and studied by Barndorff-Nielsen and Shephard (2004), Andersen et al (2004), and Huang and Tauchen (2005). Here we adopt the ratio statistics used by Huang and Tauchen (2005),

$$RJ_t(\Delta) \equiv \frac{RV_t(\Delta) - BV_t(\Delta)}{BV_t(\Delta)} \tag{6}$$

which converges to standard normal distribution, when appropriately scaled by its asymptotic variance estimate.[4]

This test has excellent size and power (Huang and Tauchen 2005), and tells us whether there is a jump occurred during a particular day, and how much the jump-squared contribution to the total realized volatility, $\sum_{j=1}^{1/\Delta} \kappa_{t,j}^2$. To gain further insight, we assume that (1) there is at most one jump per day and (2) jump size dominate return on jump days. This methodology allows us to filter out the daily actual jumps as

$$J_t = \text{sign}(r_t) \times \sqrt{RV_t(\Delta) - BV_t(\Delta)} \tag{7}$$

This method is consistent with the intuition that jumps on financial markets are rare and of large sizes. Its effectiveness is still need to be justified in finite samples studies with realistic empirical settings. This method enable us to estimate jump intensity λ_J, jump mean μ_J (including signed jump means μ_J^+ and μ_J^-), and jump standard deviation σ_J, for a given horizon (say one month or one year). Since jumps are rare, more accurate estimates of these jump risk measures should be over the longer one-year horizon. Equipped with these new technique, we are ready to reexamine the impact of jumps on credit spreads.

[4] See Appendix for implementation details and Huang and Tauchen (2005) for the finite sample performance of various competing jump detection statistics. We find that using the test level of 0.999 produces most consistent result. We also use staggered returns in constructing the test statistics, to control for the potential measurement error problem.

3 Data (to be revised)

Structural models provide an intuitive framework for identifying the determinants of credit risk changes. A firm defaults whenever the firm value hits below an exogenously or endogenously determined default boundary. Therefore the default probability of the firm is determined by all factors that affect the firm value process, the risk-free interest rate, the firm's leverage ratio, default boundary and recovery rate.

In this section we first describe the data of credit spreads, which we obtain the premium rates of credit default swaps (CDS) written on 307 reference entities. The theoretical determinants of credit spreads are then divided into three major groups: (i) firm-level equity volatility; (ii) firm's balance sheet information; and (iii) macro-financial variables.

3.1 CDS spreads

We choose to use the CDS premium as a direct measure of credit spreads in this paper. Credit default swaps are the most popular instrument in the rapidly-growing credit derivative markets.[5] A CDS provides insurance against the default risk of a reference entity (usually a third party). The protection seller promises to buy the reference bond at its par value when a credit event (including bankruptcy, obligation acceleration, obligation default, failure of pay, repudiation/moratorium, or restructuring[6]) occurs. In return, the protection buyer makes periodic payments to the seller until the maturity date of the CDS contract or until a credit event occurs. This periodic payment, which is usually expressed as a percentage (in basis points) of its notional value, is called CDS spread. Obviously, credit spread is a good measure of the default risk of the reference entity.

Compared with other measures of default risk, such as corporate-Treasury yield spreads used in many other studies, CDS spreads have several advantages.[7] First, CDS spread is a relatively pure pricing of default risk of the underlying entity. The contract is typically

[5]Credit derivatives are over-the-counter financial contracts whose payoffs are linked to changes of the credit quality of a reference entity. The credit derivatives market has grown at a stunning rate in recent years. See recent survey by British Bankers Association and the Fitch IBCA.

[6]The restructuring clause has recently been removed from the terms of standard contract and become optional.

[7]With the availability of better data sources, there have been recently burgeoning literature comparing the credit risk pricing between the cash and the derivative markets. Cossin and Hricko (2001) suggest that the determinants of CDS spreads are very similar to those in the bond market. Houweling and Vorst (2003) and Longstaff et al (2004) show that the default risk has been priced consistently between the two markets. Similarly, Hull et al (2004) find that both markets have a strong predicting power over future credit events.

traded on standardized terms.[8] By contrast, bond spreads are more likely to be affected by other factors such as the seniority, coupon payments, embedded options, guarantees, and liquidity concerns. Second, existing studies (such as Blanco et al 2004 and Zhu 2004) show that, while CDS spreads and bond spreads are quite in line with each other in the long run, in the short run the CDS spreads tend to respond more quickly to changes in credit conditions. This could be partly attributable to the fact that CDS is unfunded and faces not short-sale restriction. Third, using CDS spread can avoid the confusion on which proxy to be used as risk-free rates.[9]

The CDS data are provided by Markit, a comprehensive data source that assembles a network of industry-leading partners who contribute information across several thousand credits. On every day Markit receive quotes from its contributors for the wide range of CDS contracts. Based on the contributed quotes the daily composite quotes, which reflect the average CDS spreads offered by major market participants, are created.[10]

The dataset includes the following information: (i) information on the reference entity, including names, ratings, industry classification and geographic location; (ii) information on the CDS contract, including its maturity (from 6 months to 30 years), currency denomination, seniority and restructuring clause;[11] (iii) pricing information, including the composite quote and average recovery rate that has been used by contributors in the pricing.

In this paper we include all CDS information written on US entities (sovereign entities excluded) with currency denomination in US dollar. We also eliminate the subordinated class of contracts because of their small relevance in the database and unappealing implication in credit risk pricing. We focus on 5-year and 1-year CDS contracts with modified restructuring (MR) clause as they are the most popularly traded in the market. After matching the CDS data with other information such as equity prices and balance sheet information (discussed

[8] A standard CDS contract specifies the size, maturity, currency denomination of the contract, the definition of credit events, the pool of deliverable assets if a credit event occurs, etc.

[9] Researchers have used Treasury rates, swaps rates and repo rates as proxies for risk-free rates.

[10] There might be data problems in the contributed quotes, not only because of data-reporting errors, but also due to the fact that not every contributor is able to price all CDS contract accurately and timely as most of them are not actively traded. To avoid these problems Markit adopts three major filtering criteria: (i) an outlier criteria that removes quotes that are far above or below the average prices reported by other contributors; (ii) a staleness criteria that removes contributed quotes that do not change for a very long period; and (iii) a term structure criteria that removes flat curves from the dataset.

[11] There are four major types of restructuring clauses: old restructuring (CR), modified restructuring (MR), modified-modified restructuring (MM) and no-restructuring (XR). They differ mainly on the definition of credit events and the pool of deliverable assets if a credit event occurs. More reference is available at the website of International Swaps and Derivatives Association (http://www.isda.org).

below), we are able to obtain 307 entities in our study. The much larger pool of constituent entities relative to previous studies makes us more comfortable in our empirical results.

Table (1) (upper row) summarizes the industry and rating distributions of our sample companies. Overall they are evenly distributed across different sectors, but the ratings are highly concentrated in the single-A and triple-B categories (combined 72.5% of total). High-yield names represent only 20% of total observations, reflecting the fact that CDS on invest-grade names is still dominating the market.

The sample period starts from January 1, 2001 and ends on December 31, 2003. Although composite quotes are available on a daily basis, we choose the data frequency as monthly for two major reasons. First, balance sheet information is available only on a quarterly basis. It is difficult to examine the role of firm's balance sheets which, as theory has predicted, will have an important role in determining credit spreads. Second, as most CDS contracts are not frequently traded, the CDS dataset suffers a lot from the sparseness problem if we choose daily frequency, particularly in the early sample period. A subsequence of the choice of the data frequency is that there is not obvious autocorrelation in the empirical analysis, so the standard OLS regression is a sufficient tool to deal with our problems.

We create the monthly CDS spreads for each entity by calculating the average composite quote in the last five business days of each month, and similarly, the recovery rates related to the CDS spreads. To avoid measurement errors we remove those monthly observations for which there exist huge discrepancies (above 20%) between CDS spreads with modified-restructuring clauses and old-restructuring clauses. In addition, we also remove those CDS spreads that are higher than 20%. The data provider suggests that too high CDS spreads might be spurious for two reasons. First, liquidity tends to dry up when entities are very close to default. Therefore the data is less reliable. Second, under this situation trading is more likely to be involved with an upfront payment, which is not included in the CDS pricing. Hence CDS premium alone is not an accurate reflection of the embedded default risk.

CDS spreads exhibit substantial time variation and cross-section difference in our sample. Typically CDS spreads increased substantially in the first half of year 2002, and then declined gradually throughout the remaining sample period (see Figures 1 and 2 for an example). By rating categories the average CDS spread for single-A to triple-A entities is 45 basis point, whereas the average spreads for triple-B and high-yield names are 116 and 450 basis points, respectively.

3.2 Individual volatility

Throughout this paper we use two sets of measures for equity volatility of individual firms: historical volatility calculated from daily equity price and realized volatility calculated from intra-day equity prices. Data sources are CRSP and TAQ respectively. CRSP provides daily equity prices that are listed in the US stock market, and TAQ (Trade and Quote) includes intra-day (5-minute tick-by-tick) transactions data for securities listed on the NYSE, AMES and NASDAQ.

We adopt the methods introduced in Section 2 to calculate historical volatility and realized volatility (RV). For realized volatility we also decompose it into continuous (BV) and jump (J) components by defining "jumps" at significance levels of 50%, 99% and 99.9% (Equation 10) respectively.

The summary statistics of firm-level volatilities are reported in Table (2).[12] The average daily return volatility is between $2.1 - 2.7\%$, which is quite consistent by both measures. Historical skewness varies by entities and by sample period, but its average is not significantly different from zero over all time horizons from one week to one year. Using the truncated measure of jumps defined in Equation (8), the jump component contributes about one quarter of the total realized volatility.

Table (2) links the two measures of equity return volatility by calculating the correlation coefficients between RV and historical volatility, between BV and historical volatility, and between J and historical skewness. It is obvious that historical volatility is closely related to realized volatility over the the long-term horizon, but their correlation becomes much smaller for short sample period (such as one week). This is consistent with the prevalent observation that realized volatility is a superior measure of short-term volatility, but this gain disappears when the time horizon of interest increases. Another interesting finding is the very low correlation (slightly negative in most cases) between J and historical skewness. This is quite surprising at a first glance, since both measures have been proposed as proxy for the jump process in asset value dynamics (Equation 2). On a second thought, the two variables might have caught two different aspects of the jump process. Historical skewness measures the asymmetry of extremely upward and downward movements in asset returns.[13]

[12]All volatility measures are represented by their squared root, i.e. as the standard deviation term.

[13]Statistically, there is not clear connection between skewness and jumps. If the skewness is large and positive, it implies that an extreme upward movement is more likely to occur. On the contrary, existence of a jump process does not necessarily have any impact on skewness. For example, if upward and downward jumps are equally likely to occur, the skewness is always zero.

In contrast, J is defined as the contribution of the jump component to the realized volatility. Its magnitude is therefore related to the volatility of the jump. The two characteristics of the jump process turn out to be not correlated with each other and may have different implications on the pricing of credit risk.

We also plot the time series of the above volatility measures and jump measures for the General Motors (Figure 1) and for three rating groups (Figure 2). At a first glance, equity returns of high-yield entities are more volatile and more likely to be affected by jumps. And changes in credit spreads seem to move together with equity return volatility and jumps.

3.3 Firms' balance sheet information

The firm's balance sheet information is available from Compustat. Since it is reported on a quarterly basis, the last available quarterly observations are used to estimate monthly figures. We include the following explanatory variables:

1. Firm leverage. For each entity, market values of firm equity and book values of firm debt are used to obtain leverage ratios, which are defined as

$$leverage = \frac{100 * (Current\ debt +\ Long - term\ debt)}{Total\ equity\ +\ Current\ debt +\ Long - term\ debt}$$

   The Merton's framework predicts that a firm defaults when its leverage ratio approaches one. Therefore, it is clear that credit spreads tend to increase with leverage.

2. Return on equity (ROE). The item is defined as the ratio of pre-tax income to total equity, which measures the profitability of the reference entity. When ROE is higher, firm value is more likely to increase, therefore the default risk becomes smaller.

3. Coverage ratio. It measures the firm's ability to pay back its outstanding debt, hence tends to have a negative effect on the level of credit spreads. Its definition is

$$Coverage\ ratio = 100 * \frac{OIBD\ -\ Depreciation}{Interest\ expense\ +\ Current\ Debt}$$

   where OIBD denotes operating income before depreciation.

4. Dividend payout ratio. It is defined as the percentage ratio of dividend payout per share by ex-date divided by equity price. A higher dividend payout ratio means a

decrease in asset value, therefore a default is more likely to occur and credit spreads will increase.

Table (1) (lower left) includes summary statistics of the above variables. It is clear that there are substantial variation of firm performance in our sample dataset.

3.4 Macro-financial variables

Following the prevalent practice in existing literature, we also include the following macro-financial variables as explanatory variables of credit spreads. The data are obtained from Bloomberg.

1. Changes in business climate. We use the S&P 500 average daily return, and its volatility (in standard deviation term) in the last three months to proxy for the overall state of the economy. Higher market returns and lower market volatility mean an improved economic environment. Hence the two variables have negative and positive effects on CDS spread, respectively.

2. 3-Month Treasury rate. A higher risk-free rate increases the risk-neutral drift of the firm value process, therefore reducing the probability of default and the credit spreads. However, a higher risk-free rate may also reflect the tightening of monetary policy, which increases the firm's cost of funding and weakens its ability to pay debt. The two effects may exist together and their net impact is ambiguous.

3. Slope of the yield curve, which we define as the difference between the 10-year and 3-month US Treasury rates. An increase in yield curve slope implies an increase in expected future short rate or an improved economic condition in the future. By the same argument as above, it should lead to a decrease in credit spreads.

The summary statistics of these variables are reported in Table (1) (lower right portion).

4 Empirical evidence

Our empirical work focuses on the influence of equity return volatility and jumps on credit spreads. We first run regressions with only jump and volatility measures. Then we also include other control variables, such as ratings, macro-financial variables and balance sheet information, as predicted by the structural models and evidenced by empirical literature. Further robustness check with fixed effect and random effect does not affect result qualitatively. We also find strong interaction effect between jump/volatility measures with rating variables and firm's accounting information, suggesting that financial market risk measures are related to the fundamental health of firms' balance sheet. Finally, the apparent non-linear effect of jump and volatility risks indicates that using aggregate volatility or rating group measures may over or under estimate the true impact of volatility and jump on credit spread.[14]

4.1 Volatility and jump effect on credit spread

Table 3 reports the main findings of ordinary least squares (OLS) regressions, which explain credit spreads only by different measures of equity return volatility and/or jump measures. Regression (1) using 1-year historical volatility alone reaches R-square 45%, which is higher that the main result of Campbell and Taksler (2003, regression 8 in Table II, R-square 41%) with all volatility, ratings, accounting information, and macro-finance variables combined together. Regression (2) and (3) show that short term realized volatility also explain a significant portion of spread variations, and that combined long-run (1-year HV) and short-run (1-month RV) volatilities gives the best result of 50% R-square. The signs of coefficients are all correct—high volatility raise credit spread, and the magnitudes are all sensible—one percentage volatility shock raises credit spread about 3-9 basis points. The statistical significance will remain even if we put in all other control variables (discussed in the following subsection).

Our major contribution is to construct innovative jump measures and show that jump risks are indeed priced in CDS spreads. Regression (4) suggests that historical skewness as a measure of jump risk can have a correct sign (positive jumps reduce spreads), if we also add the historical kurtosis variable with correct sign (more jumps increases spread). This is in contrast with the counter-intuitive finding that skewness has a significantly positive impact on credit spreads (Cremers et al 2004a). However, the total predictability of traditional jump measure is still very dismal—only 3% in R-square. Our new measures of jumps—regressions (5) to (7)—give significant estimates, and by themselves explain 23% of credit spread variations. A few points are worth mentioning. First, the jump volatility has the

[14] In all regressions we focus on the 5-year CDS spread, and the results are similar for 1-year CDS and available upon request

strongest impact—raising default spread by 3-5 basis points for percentage increase. Second, when jump mean effect (-0.2 basis point) is decomposed into positive and negative parts, there is a strong asymmetry in that positive jumps only reduce spread by 0.5 basis point but negative jumps can increase spread by 1.50 basis points. This is a new finding in the empirical literature on credit risks. Third, average jump size only has mute effect (-0.2) and jump intensity can switch sign (from 0.7 to -0.6), which may be explained by controlling for positive or negative jumps.

Our new benchmark—regression (8) explains 53% of credit spread with volatility and jump variables alone. To summarize, both long-run and short-run volatilities have significant positive impacts, so do jump intensity, jump variance, and negative jump; while positive jump reduces spread.

4.2 Extended regression with traditional controlling variables

We then include more explanatory variables—credit ratings, macro-financial conditions and firm's balance sheet information—all of which are theoretic determinants of credit spreads and have been widely used in previous empirical studies. The regressions are implemented in pairs, one with and the other without measures of volatility and jump. Table 4 reports the results.

In the first exercise, we examine the extra explanatory power of equity return volatility and jump in addition to ratings. Cossin and Hricko (2001) suggest that rating information is the single most important factor in determinant CDS spreads. Indeed, our results confirm their findings that rating information alone explains about 57% of the variation in credit spreads. But this is about the same as the volatility and jump effects alone (see table 3). A remarkable result is that, volatility and jump risks can explain another 16% of the variation (R^2 increases to 73%).

The increase in R^2 is also very large in the second pair of regressions. Regression (3) shows that all other variables, including macro-financial factors (market return, market volatility, yield curve level and slope), firm's balance sheet information (ROE, firm leverage, coverage and dividend payout ratio) and the recovery rate used by price providers, combined explain an additional 6% of credit spread movements on the top of rating information (regression (3) minus regression (1)). The combined impact increase is smaller than the volatility and jump effect (16%). Moreover, regression (4) suggests that the inclusion of volatility and jump effect provides another 12% explanatory power compared to regression (3). R^2 increases to a very high level of 0.75. The results suggest that the volatility effect is independent of the impact of other structural or macro factors.

The jump and volatility effects are very robust, with the same signs and little change in magnitudes. To gauge the economic significance more systemically, it is useful to go back to the summary statistics presented earlier (Table 2). The cross-firm average of the standard-deviation of the 1-year historical volatility and the 1-month realized volatility (continuous) are 38.35% and 44.20%, respectively. Such shocks lead to a widening of the credit spreads by almost 107-128 and 73-87 basis points, respectively. Finally, consider jump variance only, one standard deviation shock (9.03%) increase credit spreads by 11-14 basis points. If we include jump intensity, positive and negative jumps, the total jump impact on credit spreads is like in the same order as the volatility impact.

Judging from the full model of regression (4), some macro-financial factors and firm variables have the expected signs of the slope coefficients. The market return has a significant negative impact on the spreads, consistent with the business cycle effect. High leverage ratio tends to increase credit spread significantly, which is consistent with structural model insight. All other variables seem to have either marginal t-statistics or economically counter-intuitive signs, and their signs & magnitudes seem to be unstable depending on whether we include volatility and jump variables or not. It is worth pointing out that the statistical significance of firm level volatility and jump risks are uniformly higher than the credit ratings, which used to be considered as the most influential factors (Cossin and Hricko 2001).

4.3 Robustness Check

We also implement a robustness check by using panel data technique with fixed and random effects (see Table (5)). Although Hausman test favors fixed effects over random effects, the regression results do not differ much between these two approaches. In particular, the slope coefficients of the individual volatility and jump variables are remarkably stable and qualitatively unchanged. On the other hand, only some of the macro-financial and firm accountings variables have consistent and significant impacts on credit spreads, including market return (negative), term spread (positive), leverage ratio (positive), and dividend payout (positive). Although notice that fixed effects or random effects can drive the rating dummies to be marginally insignificant, and the high R-square of 87% is caused by the two hundreds or so firm dummies.

4.4 Interaction with rating group and accounting information

We have demonstrated that equity volatility and jump helps to determine the credit spreads. There remain questions of whether the effect is merely a statistical phenomenon or intimately related to firm's credit standing and accounting fundamental, whether the effect is non-linear in nature, and whether different components of equity volatility have different price implications. The next three sub-sections aim to address the three issues respectively.

We first examine whether the volatility effect varies across different rating classes. Figure (2) shows that the equity return volatility and especially jump volatility are much different across rating groups. Not surprisingly, high-yield names are associated with higher risk and therefore more volatile credit spreads. This suggests that, for the same coefficient size, the economic implication of the volatility effect is more remarkable for high-yield entities. Table (6) examines this issue more seriously in regression (1) across three rating groups: triple-A to single-A names, triple-B names and high-yield entities. The results are remarkable in that the volatility/jump impact coefficients from high yield entities are typically several multiples larger than for the investment grade names. To be more precise, for long-run volatility the difference is 4.69 over 2.28, short-run volatility 2.53 over 0.37, jump intensity 2.70 over 1.19, jump volatility 3.92 over 0.58, and positive jump -1.08 over -0.24. Similarly the t-ratios of high-yield interaction terms are also much larger than those of the investment grade. In addition, these differences seem to be much larger for the realized volatility and jump risk measures, than for the historical volatility measure, which further justifies our approach of identifying volatility and jump risks separately from high frequency data.

Our measures on jumps and volatilities interact strongly with the firm specific accounting information. As shown by regression (2) in Table (6), the interactions between leverage ratio and various volatility and jump measures tend to increase the credit risk spreads, while recovery rate tends to have opposite interaction effects with long-run versus short-run volatilities and with different jump measures. Other variables like return to equity and dividend payout also have significant interactions with volatility and jump risk measures, but their signs and significances are less uniform. Nevertheless, the combined explanatory power of credit spreads reaches a R-square of 80%. These results reinforce the idea that volatility and jump risks are priced in the CDS spreads, not only because there are statistical linkages, but also because equity market trades on the firms' fundamental information. In particular, the time-varying recovery rate issue can be re-examined as the co-movement between quoted recovery rate and volatility/jump risk measures.

4.5 Nonlinear effect and credit premium puzzle

While the theory usually implies a complicated relationship between volatility and credit spreads, in empirical exercise a simplified linear relationship is often used. This linear approximation could cause substantial bias in calibration exercise and partly contribute to the under-performance of structural model, or the so-called credit premium puzzle. For instance, in Huang and Huang's (2003) paper, they used the average equity volatility within a rating class in their calibration, and found that the predicted credit spread is much lower than the observed value (average credit spreads in the rating class). However, the "averaging" of individual equity volatility could be problematic if its impact on credit spread in non-linear.

Table (7) confirms the non-linearity effect of volatility and jump. By adding the squared and cubic terms of the jump and volatility risk measures, we find that most of the nonlinear terms are statistically significant. The sign of each order may not be quite integrable, since the entire nonlinear function is driving the impact. Figure (3) illustrates the potential impact of this "Jensen inequality" problem on the performance of price prediction. If we use the mean rather than individual volatility in the calibration, the predicted credit spreads could be lower than the true average credit spread by as much as 81 (due to 1-year historical volatility) and 33 (due to 1-month realized volatility) basis points, which goes a long way to resolve the under-prediction part of the credit premium puzzle. Likewise, using the mean rather than individual jump intensity and volatility, the predicted CDS spreads would be 13 basis points higher (due to 1-year jump intensity), cancelling out 13 basis points lower (due to 1-year jump volatility). Most interesting is the signed jumps—in negative region averaging may under-predict credit spreads but in positive region over predict, with overall small over-prediction of 4 basis points. In short, averaging volatilities over individual firms produces significant underfitting of credit yield curve, while averaging jumps may cancel each other out the nonlinear effect.

5 Simulation evidence from stylized models

Our findings of predictability of volatility and jump risks for credit spreads are qualitatively consistent with the structural model implications. At the same time, we know that the structural approaches have difficulties in matching the observed credit spreads. In this section, we examine the capability of a standard model of Merton (1974) and a stochastic volatility model in replicating the forecast-ability of historical volatility for credit premium.

We also illustrate the flexibility of credit yield curves from the time-varying volatility model.

5.1 A simple model with time-varying volatility

Given constant risk-free rate r and constant default boundary K, firm value process V_t with stochastic volatility ν_t,

$$\begin{aligned} \frac{dV_t}{V_t} &= (\mu_t - \delta)dt + \sigma_t dW_{1t} &(8)\\ d\sigma_t^2 &= \beta(\alpha - \sigma_t^2)dt + \gamma\sqrt{\sigma_t^2}dW_{2t} &(9) \end{aligned}$$

where the innovations in value and volatility processes are correlated as $\mathrm{corr}(dW_{1t}, dW_{2t}) = \rho dt$. Existing model usually assumes stochastic interest rate and time varying leverage, but keeps the volatility constant. Assuming that all assets are traded and no-arbitrage implies the existence of an equivalent martingale measure,

$$\begin{aligned} \frac{dV_t}{V_t} &= (r - \delta)dt + \sigma_t dW_{1t}^* &(10)\\ d\sigma_t^2 &= \beta^*(\alpha^* - \sigma_t^2)dt + \gamma\sqrt{\sigma_t^2}dW_{2t}^* &(11) \end{aligned}$$

with volatility risk premium ξ. Equity price S_t of the firm can be viewed as an European call option with matching maturity T for debt D_t with face value K. The solution is given by Heston (1993),

$$S_t = V_t P_1^* - Ke^{-r(T-t)}P_2^* \tag{12}$$

where P_1^* and P_2^* are risk-neutral probabilities. In the context of Merton (1974) model, these probabilities are from normal distributions with a constant asset volatility parameter $\sigma_t^2 = \alpha$, i.e., $S_t = V_t N_1^* - Ke^{-r(T-t)}N_2^*$. Therefore the debt value of both models can be expressed as $D_t = V_t - S_t$, and its price is $P_t = D_t/K$. The credit default spread is given by

$$R_t - r = -\frac{1}{T-t}\log(P_t) - r \tag{13}$$

To justify our empirical findings, we need to show (at least) inside simulation that the current credit spread is related to past volatility of equity (S_t), its nonlinear squared term, and interaction with value (V_t/K). Note that within Merton (1974) model, although the asset value volatility is constant, the equity volatility is time-varying, due to the time-varying non-linear delta function. With the stochastic volatility model, both the asset volatility and the delta function are time-varying.

5.2 Simulation evidence from structural models

In the Monte Carlo exercise, we set the annualized parameters as following: $\beta = 0.10$, $\alpha = 0.25$, $\gamma = 0.10$, $\xi = -0.20$, and $\rho = -0.50$. To focus on stochastic volatility, we set non-essential parameters to zero, i.e., $\mu_t = \delta = r = 0$. In addition, the starting value of the asset is set at 100 and the debt boundary is set at 60. For each random sample, we simulate 10 years of daily realization, and then calculate the monthly variables similar to the empirical exercise. We perform regression analysis between current month credit spread and lagged one year volatility, nonlinear volatility term, and interaction between volatility and asset value change. The total Monte Carlo replications is 2000 random samples. The results are shown in the following Table (8).

It is clear that even with the Merton (1974) model, equity volatility and volatility squared show strong predictability for credit risk premia, with R-square around 0.57 and positive signs largely consistent with our empirical findings. Also note that the interaction term of equity volatility and firm value change is negatively impacting the credit spread, which is also consistent with our empirical evidence in Table 6 on historical volatility and recovery rate. It should be point out that within Merton (1974) model the asset volatility is constant. However the equity volatility is time-varying due to the fact that the nonlinear delta function is depending on the time-varying firm value. Our justification of time-varying volatility effect on credit spread is completely opposite to that of Campbell and Taksler (2003), who assume that debt is risk-free and that delta function is constant.

As seen from Table (8), a stochastic volatility model produces similar predictability R-squares and coefficient signs, for the default risk premium from equity volatility, nonlinear term, and interaction term. However, coefficient magnitudes are 2-10 times larger than the constant volatility model, and t-ratios parameter estimates are also slightly higher than the Merton (1974) model. Both the nonlinear and the interaction terms have similar sign as we discovered in the empirical exercise. Also, the R-square of 0.51-0.57 from volatility and R-square of 0.72-0,75 from volatility and interaction combined, match quite well as what we have found in the actual CDS prediction regressions.

Figure (4) illustrate the difference between the credit yield curves from a stochastic volatility model and the Merton (1974) model. In the benchmark case (upper left), both models have the same unconditional volatility. The Merton (1974) model credit curve is very flat (less than 200 basis points) while the stochastic volatility yield curve is much steep (close to 1000 basis points). By changing the underlying model parameters, the credit curve from time-varying volatility model can assume a variety shapes—flat, steep, hump, straight, etc.. Such a flexibility may potentially overcome under-fitting problem of the standard structural model, and may price the individual credit spread more accurately.

6 Conclusions

In this paper we use a large dataset to examine the impact of theoretic determinants, particularly firm-level equity return volatility and jumps, on the level of credit spreads in the credit-default-swap market. Our results find strong volatility and jump effect, which explains another 12% of the movements in credit spreads after controlling for rating information and other structural factors. In particular, when all these control variables are included, equity volatility and jumps are still the most significant factors, even more than the rating informations. This effect is economically significant and remains robust to a number of variants of the estimation method. The volatility and jump effects are the strongest for high-yield entities, and they also exhibit strong non-linearity for investment-grade names. We expect that the non-linearity could be used to explain the under-performance of structural models in the existing literature.

We adopt an innovative approach to identify return jumps of individual firms, which enables us to assess the impact of various jump risks (intensity, variance, negative jumps) on default risk premia. Our results on jumps are statistically and economically significant, which contrasts the typical mixed finding in literature using historical or implied skewness as jump proxy.

Our study is only a first step towards improving our understanding of the impact of volatility and jumps on credit risk pricing. Calibration exercise that takes into the time variation of volatility & jump risks and the non-linear effect could be a promising direction to explore for resolving the so-called credit premium puzzle. Related issues, such as the connections between equity volatility and asset volatility, also worth more attention from academic researchers and practitioners.

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7 Appendix (to be completed)

Table 1: **Summary Statistics:** (i) sectoral distribution of sample entities; (ii) distribution of credit spread observations by ratings; (iii) firm-specific information; (iv) macro-financial variables.

By sector	**number**	**percentage (%)**	**By rating**	**number**	**percentage (%)**
Communications	20	6.51	AAA	219	2.15
Consumer cyclical	63	20.52	AA	559	5.48
Consumer Stable	55	17.92	A	3052	29.92
Energy	27	8.79	BBB	4394	43.07
Financial	23	7.49	BB	1321	12.95
Industrial	48	15.64	B	544	5.33
Materials	35	11.40	CCC and below	112	1.10
Technology	14	4.56			
Utilities	18	5.88			
Not specified	4	1.30			
Total	*307*	*100*	*Total*	*10201*	*100*

Firm-specific variables	**Mean**	**Std. dev.**	**Macro-financial variables**	**Mean (%)**	**Std. dev.**
Recovery rates (%)	39.50	4.63	S&P 500 return	-13.15	14.72
Return on equity (%)	4.50	6.80	S&P 500 vol	22.42	2.90
Leverage ratio (%)	48.81	18.64	3-M Treasury rate	2.04	1.24
Coverage ratio (%)	125.94	209.18	Term spread	2.51	0.96
Div. Payout ratio (%)	0.41	0.47			
5-year CDS spread (bps)	172	230			
1-year CDS spread (bps)	157	236			

Table 2: **Summary statistics of equity returns**

2.A Historical measures (%)						
Variables	*1-month*		*3-month*		*1-year*	
	mean	*std dev*	*mean*	*std dev*	*mean*	*std dev*
Hist ret	3.12	154.26	1.58	87.35	-3.22	42.70
Hist vol (HV)	38.35	23.91	40.29	22.16	43.62	18.57
Hist skew (HS)	0.042	0.75	-0.061	0.93	-0.335	1.22
Hist kurt (HK)	3.36	1.71	4.91	4.25	8.62	11.78

2.B Realized measures (%)						
Variables	*1-month*		*3-month*		*1-year*	
	mean	*std dev*	*mean*	*std dev*	*mean*	*std dev*
RV	45.83	25.98	47.51	24.60	50.76	22.49
RV(C)	44.20	25.85	45.96	24.44	49.37	22.25
RV(J)	7.85	9.59	8.60	8.88	9.03	8.27

2.C Correlations			
Variables	*1-month*	*3-month*	*1-year*
(HV, RV)	0.87	0.90	0.91
(HV, RV(C))	0.87	0.89	0.90
(HS, RV(J))	0.006	0.014	0.009
(HK, RV(J))	0.040	0.025	0.011

Notes: (1) Throughout all the tables, historical volatility (HV), realized volatility (RV) and its continuous (RV(C)) and jump (RV(J)) components are represented by their standard deviation terms; (2) The continuous and jump components of realized volatility are defined by Huang & Tauchen (2005) (Equations (9) and (10)) at a significance level of 99.9%.

Table 3: **Baseline regression: explaining 5-year CDS spreads using individual equity volatilities and jumps**

	Dependent variable: 5-year CDS spread (in basis point)							
Explanatory variables	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**
Constant	-207.22	-91.10	-223.11	147.35	169.29	85.66	20.80	-273.46
	(36.5)	(18.4)	(40.6)	(39.6)	(50.3)	(20.8)	(3.9)	(42.8)
1-year HV	9.01		6.51					6.90
	(72.33)		(40.2)					(38.8)
1-year HS				-10.23				
				(3.2)				
1-year HK				2.59				
				(7.5)				
1-month RV		6.04	2.78					
		(60.5)	(23.0)					
1-month RV(C)								2.37
								(20.2)
1-year JI					0.71		-0.65	1.46
					(9.5)		(5.0)	(13.4)
1-year JM					-0.21			
					(15.8)			
1-year JV					5.21		3.44	1.20
					(32.9)		(14.4)	(6.3)
1-year JP						-0.45	-0.67	-0.62
						(7.3)	(9.8)	(11.8)
1-year JN						1.47	1.56	0.45
						(22.9)	(23.6)	(8.3)
Adjusted R^2	0.45	0.37	0.50	0.03	0.19	0.14	0.23	0.53
Obs.	6342	6353	6337	6342	6064	6328	6064	6064

Notes: (1) t-statistics in the parenthesis; (2) JI, JM, JV, JP and JN refer to the jump intensity, jump mean, jump variance, positive jumps and negative jumps as defined in section 2.

Table 4: **Regressions with ratings, individual equity volatilities, macro-financial variables, firm-specific variables and recovery rates**

Regression	**1**		**2**		**3**		**4**	
1-year Return			-0.81	(17.5)			-0.67	(13.6)
1-year HV			2.49	(15.9)			2.94	(17.3)
1-month RV(C)			1.97	(19.7)			1.65	(16.0)
1-year JI			0.94	(10.4)			1.10	(11.6)
1-year JV			1.22	(8.1)			1.57	(10.7)
1-year JP			-0.67	(15.7)			-0.62	(14.7)
1-year JN			0.37	(8.3)			0.26	(6.1)
Rating (AAA)	33.48	(2.1)	-166.67	(11.6)	-71.34	(1.3)	-205.34	(4.4)
Rating (AA)	36.72	(4.7)	-146.40	(18.4)	-76.05	(1.4)	-184.05	(4.1)
Rating (A)	56.15	(16.0)	-132.42	(22.2)	-61.11	(1.1)	-177.01	(3.9)
Rating (BBB)	141.29	(50.4)	-68.60	(10.4)	12.74	(0.2)	-121.13	(2.7)
Rating (BB)	428.21	(73.7)	142.66	(16.1)	278.61	(5.1)	84.96	(1.9)
Rating (B)	745.31	(79.8)	349.20	(27.7)	544.38	(9.9)	239.69	(5.3)
Rating (CCC & -)	1019.60	(36.5)	552.25	(21.7)	503.92	(7.4)	98.61	(1.8)
S&P 500 return					-1.86	(7.5)	-1.23	(8.4)
S&P 500 vol					4.46	(3.9)	-3.03	(3.1)
Short rate					17.36	(2.9)	2.70	(0.5)
Term spread					26.23	(3.5)	16.13	(2.7)
Recovery rate					-2.59	(5.4)	0.12	(0.3)
ROE					-3.89	(12.5)	-0.91	(3.4)
Leverage ratio					0.53	(4.3)	0.70	(6.9)
Coverage ratio					-0.023	(2.1)	-0.002	(0.2)
Div. payout ratio					3.74	(0.9)	12.86	(3.6)
Adjusted R^2	0.57		0.73		0.63		0.75	
Obs.	6124		5784		4574		4366	

Notes: (1) t-statistics in the parenthesis.

Table 5: **Robustness check**

	Fixed Effect				**Random Effect**			
	1		**2**		**1**		**2**	
constant					-97.72	(8.0)		
1-year Return			-0.73	(16.2)			-0.70	(15.7)
1-year HV	2.96	(16.4)	0.82	(4.4)	3.50	(20.4)	1.17	(6.5)
1-month RV(C)	2.61	(32.5)	1.67	(21.0)	2.60	(32.5)	1.69	(21.4)
1-year JI	0.10	(0.7)	0.10	(0.7)	0.34	(2.6)	0.37	(2.8)
1-year JV	0.96	(0.7)	1.17	(8.4)	0.91	(6.0)	1.17	(8.4)
1-year JP	-0.71	(15.2)	-0.52	(11.8)	-0.67	(14.6)	-0.50	(11.6)
1-year JN	0.52	(9.8)	0.38	(7.9)	0.60	(11.6)	0.42	(9.1)
Rating (AAA)							-206.72	(4.4)
Rating (AA)			19.70	(0.5)			-189.42	(4.4)
Rating (A)			52.77	(1.6)			-149.84	(3.9)
Rating (BBB)			79.91	(2.4)			-105.95	(2.7)
Rating (BB)			109.01	(3.1)			-27.45	(0.7)
Rating (B)			148.79	(3.8)			52.08	(1.3)
Rating (CCC & -)							150.91	(1.5)
S&P 500 return			-1.12	(10.1)			-1.14	(10.4)
S&P 500 vol			-2.43	(3.1)			-1.98	(2.6)
Short rate			7.81	(2.0)			10.10	(2.6)
Term spread			18.34	(4.1)			19.80	(4.4)
Recovery rate			0.27	(0.7)			0.23	(0.6)
ROE			0.21	(0.8)			0.05	(0.2)
Leverage ratio			1.05	(3.7)			1.32	(5.4)
Coverage ratio			-0.02	(1.9)			-0.013	(1.2)
Div. payout ratio			36.52	(7.8)			33.84	(7.5)
Adjusted R^2	0.81		0.87		——		——	
Obs.	6064		4366		6064		4366	

Notes: (1) t-statistics in the parenthesis.

Table 6: **Interactive effects of equity volatilities and jumps**

Regression	**1**		**2**	
	coef	*t-stat*	*coef*	*t-stat*
Constant	-64.88	(1.5)	49.55	(0.8)
1-year Return	-0.49	(10.3)	-0.56	(11.9)
HV*Group 1	2.28	(8.1)	12.29	(9.0)
HV*Group 2	2.64	(12.0)	12.81	(9.6)
HV*Group 3	4.69	(22.4)	14.44	(10.7)
RV(C)*Group 1	0.37	(2.1)	-11.86	(12.9)
RV(C)*Group 2	1.77	(12.2)	-10.37	(11.4)
RV(C)*Group 3	2.53	(14.3)	-9.60	(10.3)
JI*Group 1	1.19	(5.2)	2.31	(2.6)
JI*Group 3	2.70	(16.4)	4.26	(4.7)
JV*Group 1	0.58	(1.9)	2.92	(2.1)
JV*Group 3	3.92	(18.6)	5.90	(4.6)
JP*Group 1	-0.24	(2.3)	-1.87	(4.6)
JP*Group 2	-0.29	(4.6)	-1.84	(4.7)
JP*Group 3	-1.08	(16.1)	-2.43	(6.2)
S&P 500 return	-1.38	(9.7)	-1.39	(10.3)
S&P 500 vol	-2.91	(3.1)	-3.17	(3.6)
3M Treasury rate	4.86	(1.0)	-6.66	(1.4)
Term spread	8.43	(1.4)	8.59	(1.6)
Recovery rate	0.18	(0.5)	1.37	(1.3)
ROE	-0.91	(3.6)	-3.81	(5.5)
Leverage ratio	0.73	(7.4)	-2.03	(6.9)
Coverage ratio	-0.01	(0.5)	0.01	(0.5)
Div payout ratio	12.84	(3.7)	12.71	(1.1)
HV*Recovery			-29.16	(9.5)
HV*ROE			7.41	(5.0)
HV*Leverage			2.88	(3.4)
RV(C)*Recovery			27.42	(13.0)
RV(C)*ROE			-3.52	(2.6)
RV(C)*Leverage			2.31	(3.8)
RV(C)*DivPayout			36.01	(2.5)
JV*Recovery			-5.96	(2.0)
JP*Recovery			4.16	(4.6)
JP*ROE			2.73	(3.6)
JN*Leverage			1.32	(4.9)
Adjusted R^2	0.77		0.80	
Obs.	4366		4366	

Notes: (1) " Group 1" is a dummy variable that incudes ratings AAA, AA ad A; "Group 2" is a dummy variable of rating BBB; and "Group 3" is a dummy variable that includes ratings BB, B, CCC and below. Interaction terms only includes those with t-ratios larger than 2.0 in the second regression.

Table 7: **Nonlinear effects of equity volatilities and jumps**

Regression	**1**		**2**	
	coef	*t-stat*	*coef*	*t-stat*
Constant	-28.35	(1.4)		
1-year Return	-0.25	(4.4)	-0.68	(14.1)
HV	-3.14	(2.4)	-5.34	(4.2)
HV^2	2.13	(6.6)	1.86	(5.4)
HV^3	-0.11	(4.6)	-0.11	(3.9)
RV(C)	0.25	(0.5)	0.18	(0.4)
$RV(C)^2$	0.37	(3.6)	0.26	(2.6)
$RV(C)^3$	-0.01	(2.8)	-0.01	(1.3)
JI	3.57	(6.1)	2.76	(5.9)
JI^2	-0.39	(3.9)	-0.44	(5.2)
JI^3	0.01	(2.6)	0.03	(5.1)
JV	2.18	(3.9)	0.36	(0.8)
JV^2	-0.40	(3.5)	0.26	(3.0)
JV^3	0.02	(4.3)	-0.01	(2.9)
JP	-0.67	(3.6)	-0.46	(3.0)
JP^2	-0.01	(0.7)	-0.01	(1.0)
JP^3	0.001	(1.8)	0.0003	(1.1)
JN	-0.41	(2.1)	-0.29	(2.0)
JN^2	0.09	(6.2)	0.06	(5.2)
JN^3	-0.002	(6.4)	-0.001	(5.1)
Rating (AAA)			-107.06	(2.3)
Rating (AA)			-91.44	(2.0)
Rating (A)			-79.11	(1.7)
Rating (BBB)			-19.78	(0.4)
Rating (BB)			184.36	(4.0)
Rating (B)			301.08	(6.5)
Rating (CCC & -)			254.63	(4.5)
S&P 500 return			-1.20	(8.4)
S&P 500 vol			-0.09	(0.1)
3M Treasury rate			14.35	(3.0)
Term spread			26.64	(4.6)
Recovery rate			-0.06	(0.2)
ROE			-1.20	(4.7)
Leverage ratio			0.71	(7.3)
Coverage ratio			-0.001	(0.1)
Div payout ratio			7.09	(2.1)
Adjusted R^2	0.57		0.78	
Obs.	6064		4366	

Notes:

Table 8: **Monte Carlo evidence on the predictability of CDS spreads**

Model	Merton (1974) Model				Stochastic Volatility Model			
Volatility	1.14			1.10	5.78			5.71
	(1.54)			(1.60)	(1.91)			(2.06)
Volatility^2		6.19				66.76		
		(2.04)				(2.31)		
Vol×Asset Value Change			-0.41	-0.35			-1.02	-0.95
			(1.19)	(1.65)			(1.51)	(1.91)
R-Square	0.53	0.53	0.25	0.75	0.51	0.51	0.25	0.72
	(2.37)	(2.39)	(1.54)	(4.55)	(2.19)	(2.16)	(1.51)	(4.24)

Notes: Bootstrap t-ratios are reported in the parentheses.

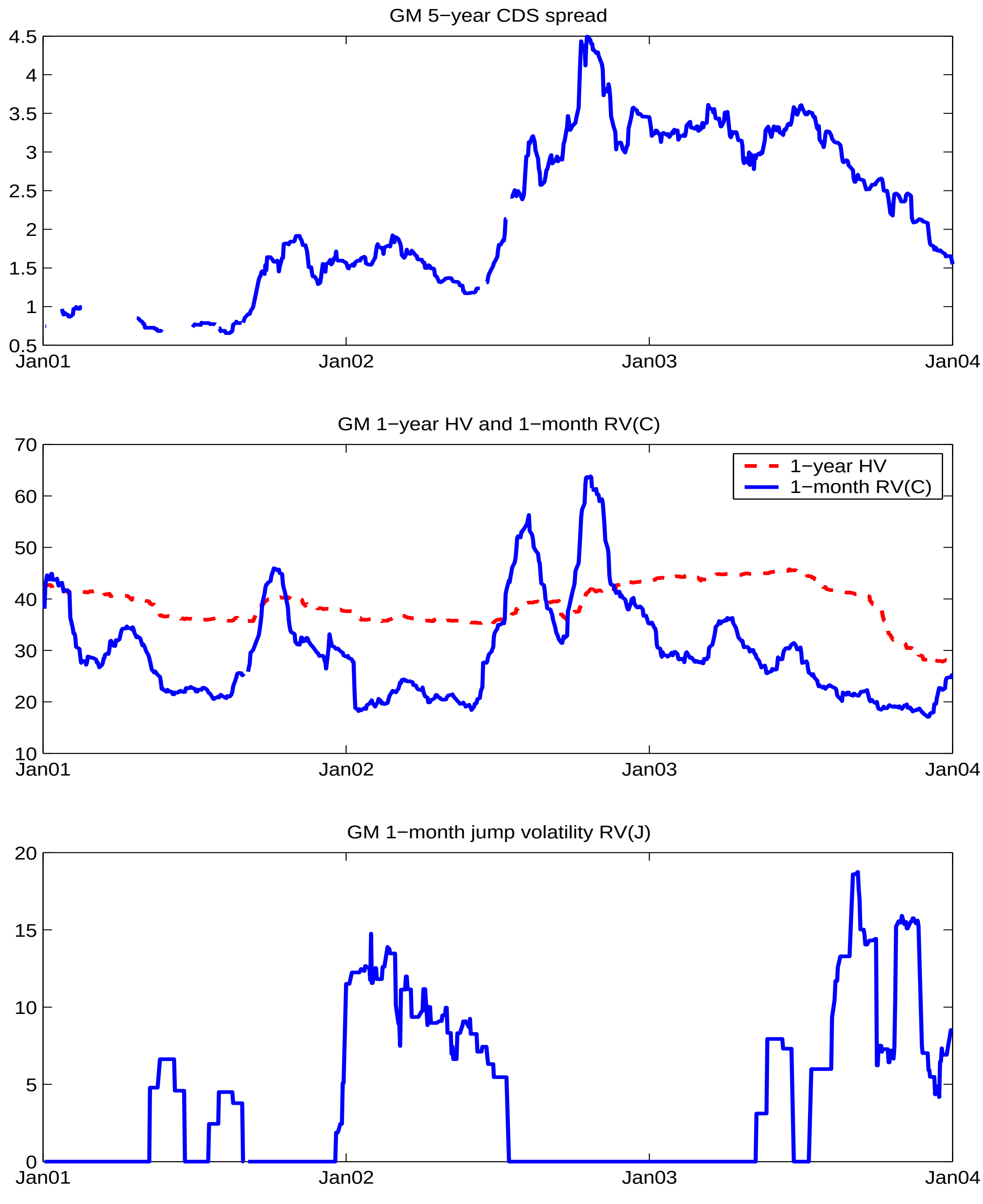

Figure 1: An example - General Motors

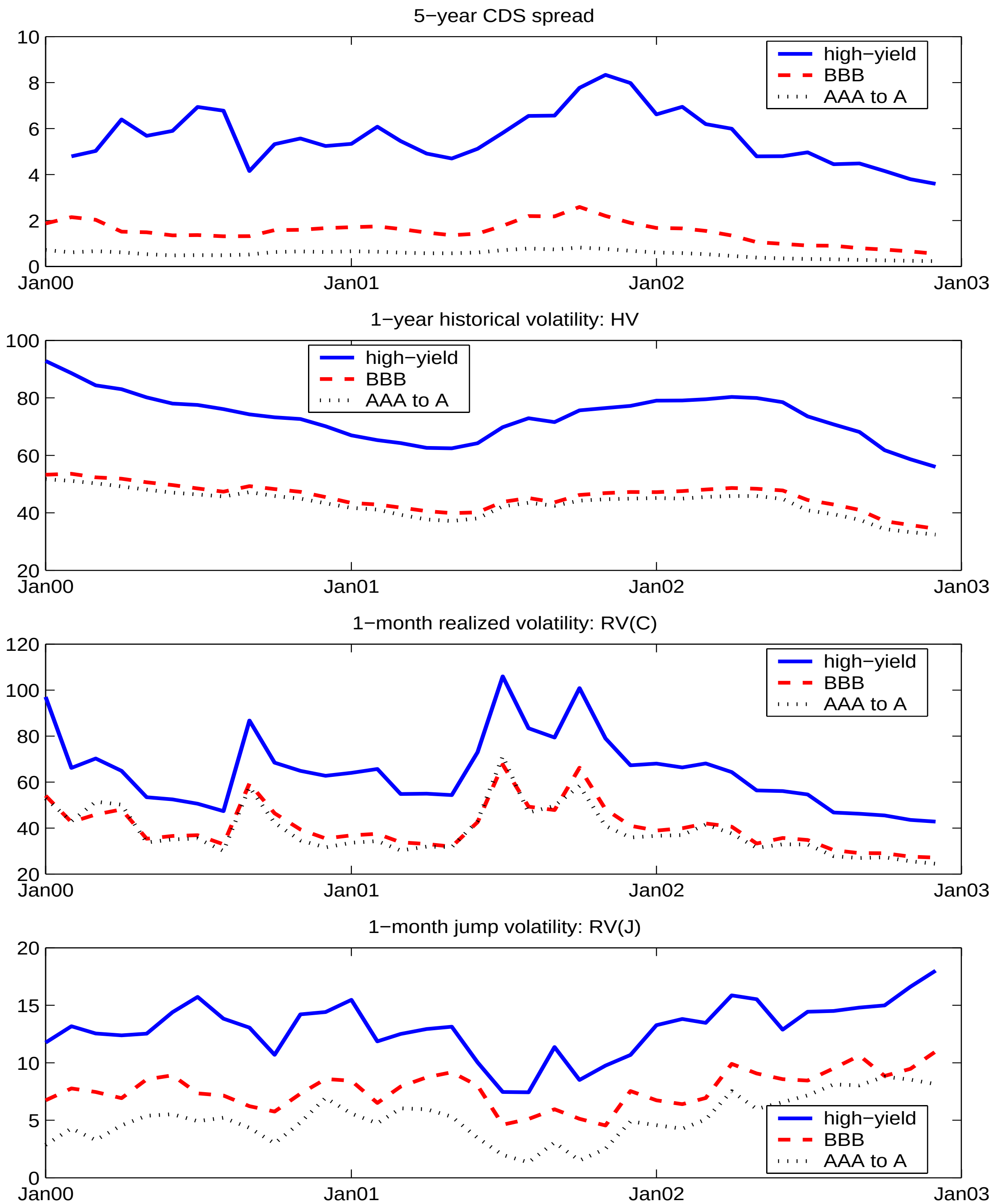

Figure 2: CDS spreads and volatility risks by rating groups

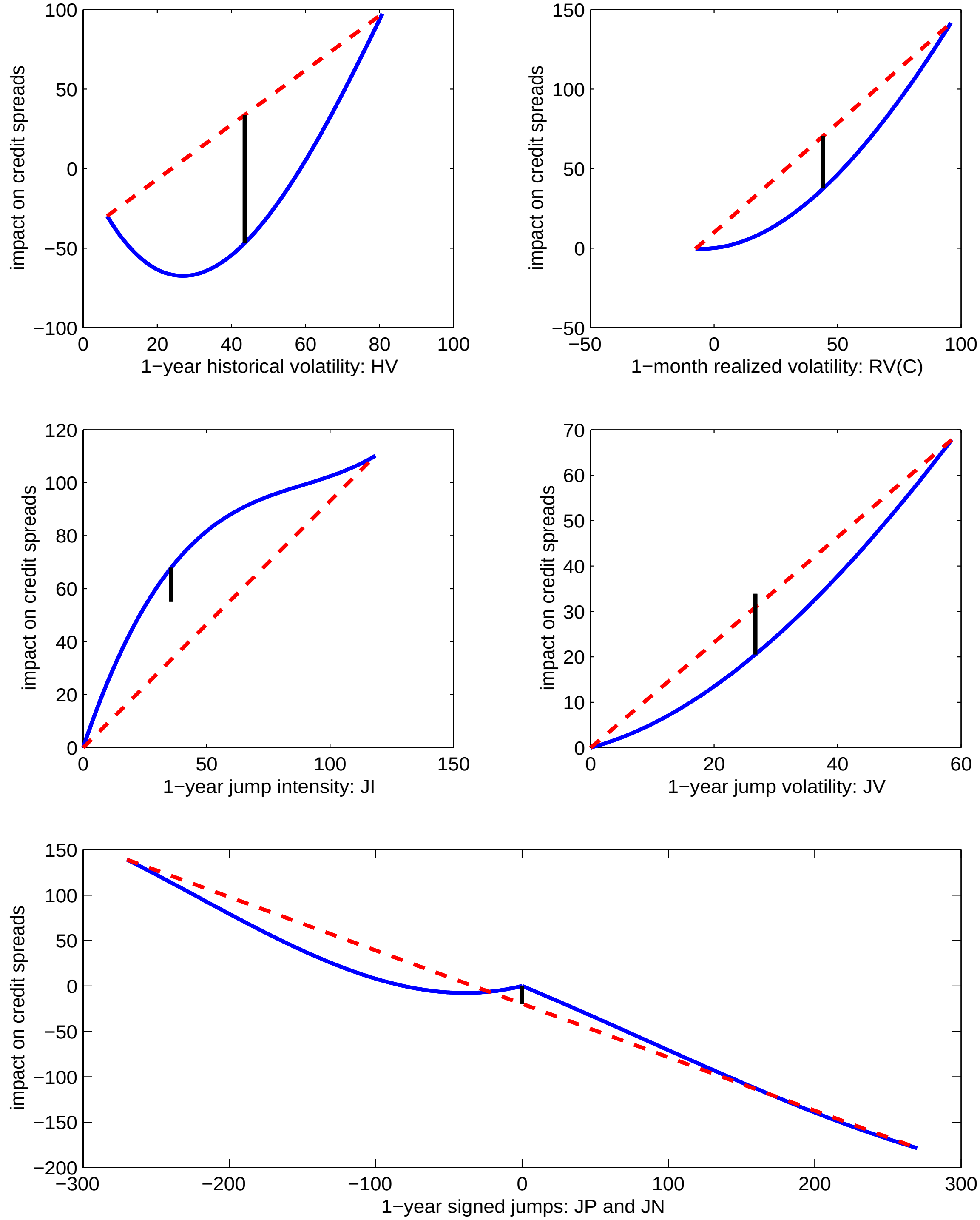

Figure 3: Nonlinear effect of individual volatility

Note: The illustration is based on regression results in Table 7 (regression 1). X-axis variables have the value range of [mean $\pm$ 2$*$ standard deviation].

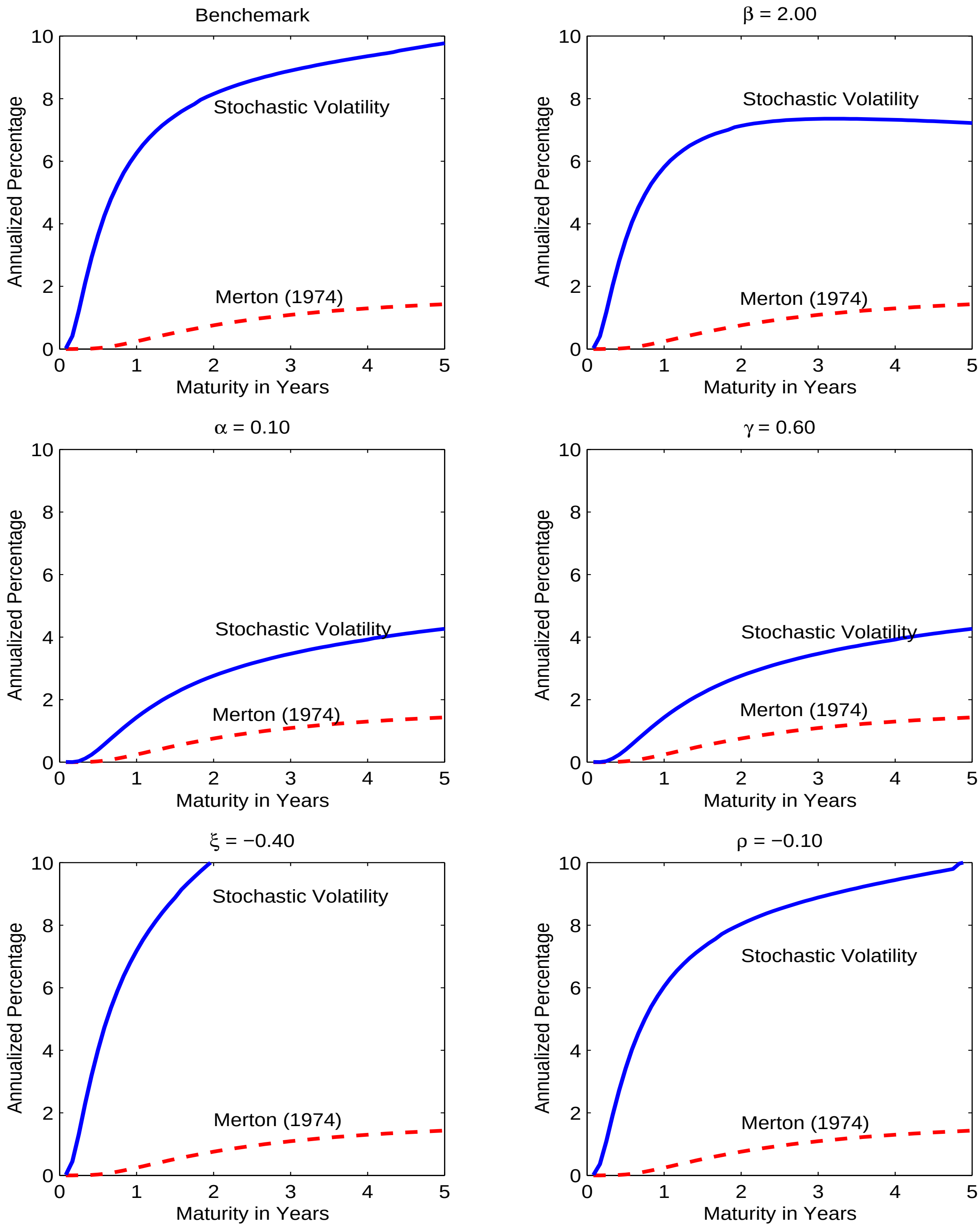

Figure 4: Simulated term structure of credit spread

Note: The benchmark parameter setting is $\beta = 0.10$, $\alpha = 0.25$, $\gamma = 0.10$, $\xi = -0.20$, and $\rho = -0.50$.